SensAI+Expanse
Emotional Valence Prediction Studies with Cognition and Memory Integration

Nuno A. C. Henriques

BioISI
Faculdade de Ciências
Universidade de Lisboa
Portugal
nach@edu.ulisboa.pt

Helder Coelho

BioISI
Faculdade de Ciências
Universidade de Lisboa
Portugal
hcoelho@di.fc.ul.pt

Leonel Garcia-Marques

CICPSI
Faculdade de Psicologia
Universidade de Lisboa
Portugal
garcia_marques@sapo.pt

Abstract—The humans are affective and cognitive beings relying on memories for their individual and social identities. Also, human dyadic bonds require some common beliefs, such as empathetic behaviour for better interaction. In this sense, research studies involving human-agent interaction should resource on affect, cognition, and memory integration. The developed artificial agent system (SensAI+Expanse) includes machine learning algorithms, heuristics, and memory as cognition aids towards emotional valence prediction on the interacting human. Further, an adaptive empathy score is always present in order to engage the human in a recognisable interaction outcome. The developed system encompass a mobile device embodied interacting agent (SensAI) plus its Cloud-expanded (Expanse) cognition and memory resources. The agent is resilient on collecting data, adapts its cognitive processes to each human individual in a learning best effort for proper contextualised prediction. The current study make use of an achieved adaptive process. Also, the use of individual prediction models with specific options of the learning algorithm and evaluation metric from a previous research study. The accomplished solution includes a highly performant prediction ability, an efficient energy use, and feature importance explanation for predicted probabilities. Results of the present study show evidence of significant emotional valence behaviour differences between some age ranges and gender combinations. Therefore, this work contributes with an artificial intelligent agent able to assist on cognitive science studies, as presented. This ability is about affective disturbances by means of predicting human emotional valence contextualised in space and time. Moreover, contributes with learning processes and heuristics fit to the task including economy of cognition and memory to cope with the environment. Finally, these contributions include an achieved age and gender neutrality on predicting emotional valence states in context and with very good performance for each individual.

Keywords—emotional valence prediction; context; cognition; memory; human-agent interaction.

I. INTRODUCTION

The human agents may be seen like self-consciousness, emotion-driven, cognitive beings with a bond between the evolutionary way of emotions and their supporting physical structure, as proposed in [1]. In a sense, an agent's behaviour depends on its affective states besides cognition to cope with the environment. Thus, the ability to predict some dimension of those affects would undoubtedly be of great value towards better adaptation and interaction with others. Furthermore, an artificial agent, like in humans, may be conceived with a decision process influenced by facts, reason, memories [2] and emotional pressure for the basic needs to the entity's homeostasis [3]. Additionally, using the concept of empathy [4][5] as a starting point for two-agent bonding may bring better dyadic interaction and communication. Therefore, an artificial agent adjusting empathetically towards the interacting human current behaviour and affective state may be conceived [6][7]. Further, Human-Agent Interaction (HAI) should be open to each entity own perception, such as the perceived human affective states in a multimodal approach [8][9]. Accordingly, the use of a wearable or mobile device, such as a smartphone seems suitable for the task of collecting data towards affect sensing and reasoning. Twenty years ago, the American College of Medical Informatics (ACMI) has already approached the subject during the 1998 Scientific Symposium: "Monitor the developments in emerging wearable computers and sensors — possibly even implantable ones — for their potential contribution to a personal health record and status monitoring" [10]. Currently, the mobile device as a sensing tool for behavioural research is thriving with active discussions [11][12] including exploration on correlates between sensors' data and depressive symptom severity [13].

This paper describes the SensAI+Expanse system ability to predict human emotional valence states in geospatial and temporal context without evidence of any bias regarding demographics, such as age and gender. This prediction ability is supported by cognition and memory integration in learning mechanisms within an adaptive process. Further, human population in current study comprise distinct behaviour, age, gender, and place of origin. Meaning, the need for proper adaptation on reasoning about each individual and respective collected data in order to assure demographics neutrality. Accordingly, the system developed for the affective studies encompasses an integration of cognition and memory resources distributed between a smartphone embodied agent (SensAI) and its Cloud-expanded (Expanse) continuity. SensAI collects data from multimode sources, such as (a) device sensors (e.g., Global Positioning System (GPS)); (b) current timestamp in

user calendar time zone; and (c) human text writings from in-application diary and social network posts (e.g., Twitter). These written texts in (c) will be subjected to a rule-based lexical processing [14] in order to obtain a valence value, i.e., instantaneous sentiment analysis on demand with efficient energy use. The human reports emotional valence ground truth by means of three available buttons regarding positive, neutral, and negative sentiment classes. Simultaneously, an empathy score progress bar is visible during this interaction (Figure 1) and may change on events, such as the human reporting frequency. The score decays over time and it is designed to be the human-agent current value of empathy. Complementary, the available algorithms and heuristics included in Expanse are used by a pipeline process in order to reason about the data set of each human individual. These machine learning services comprise (a) unsupervised algorithms, such as location clustering parameters auto discovery; and (b) supervised ones, such as learning hyperparameters auto tuning. Regarding the learning model and evaluation metric, the choice is based on a previous study [15] where Extreme Gradient Boosting and F1 score achieved good results for several data sets. As depicted in Figure 2, the prediction performance of the agent achieved a score greater than 0.9 for almost two thirds of the population (31 eligible out of 49 from a total of 57), one third distributed between 0.7 (exclusive) and 0.9, with only one subject scoring slightly less than 0.7 (0.68).
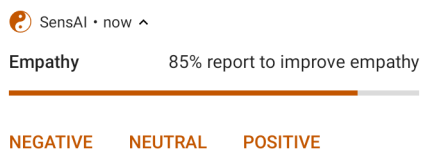

Figure 1. Empathy score notification and emotional valence report buttons.
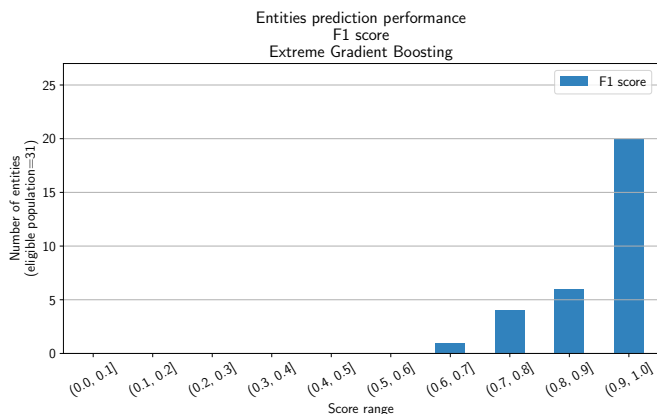

Figure 2. Prediction performance on all individuals by F1 score range.

This first section introduced the current investigation purpose and the work done so far. Next, Section II briefly describes the cognitive and memory mechanisms in place for the developed system reasoning capabilities on emotional valence prediction. Section III describes the research study

followed method and the achieved results, including the scope restrictions of this and similar studies using smartphone sensing. Finally, Section IV summarises the outcomes and presents a future perspective.

II. COGNITION AND MEMORY IN SENSAI+EXPANSE

In order to enable SensAI+Expanse as a trustable research tool for affective studies, this section briefly describes the achieved cognition and memory integration in the developed system. In a sense, this agent is more than an instrument by means of some bio-inspired concepts on its design and implementation. Regarding natural brains, to some extent may be seen as mainly about cognitive processing and memory use towards learning in order to adapt and survive. All this, of course, besides identity, social and cultural aspects. Moreover, emotions in humans are of great importance by helping on decision-making and also with the persistence of episodic memories, amongst other useful regulations [16][17]. Simultaneously, "Forgetting to remember" [18] is required to sustain adequate processing and storage when coping with the information stream that flows through perception sensors. Thus, the concept of cognitive economy is introduced comprising some exclusions from memory to foster savings by means of (a) sustaining last collected data value without change from a sensor during a well-defined time interval (e.g., 15 minutes); and (b) discarding data below relevant thresholds (e.g., location changed less than 10 meters). The resulting information gaps in (a) are filled *a posteriori* in Expanse cognition. This reconstruction is done strictly with the same time interval values used by SensAI thus avoiding any data bias.

As already referred, adaptive mechanisms including cognitive and memory ones are described in a previous paper [15]. Although, there are some of this Automated Machine Learning (AutoML) process aspects relevant to emphasise once more. Regarding system communication, SensAI and its Expanse are connected through an end-to-end secure Web service. The data flows mainly from the mobile device sensors collected by SensAI to the Expanse storage for posterior processing in a pipeline. SensAI has in-device reasoning and memory abilities yet the Expanse does the heavy work by means of several adaptive mechanisms regarding collected data from human behaviour. In the end, the system functions as a distributed, fault-tolerant, mobile and Cloud-based artificial intelligent agent. It may be used as a robust, continuously, online research tool for gathering and processing human emotional valence data towards contextualised predictions, and also affective studies.

A. SensAI

The mobile device agent is embodied, encompassing several functions as a whole, towards proper interaction, data collecting, reasoning, and storage. The ground truth values for emotional valence prediction are reported by humans. The main interface includes three emoticon in buttons representing

the available discrete valence classes of negative, neutral, and positive, as in the persistent notification (Figure 1). Further, this mechanism is robust to interaction bias, such as high-frequency repeated button (emoticon) clicks. Also, to cases of mistaken valence reported and promptly corrected by an additional hit on a different class. Moreover, a simple yet effective heuristic of accounting only for the last hit during a defined short time interval is in place. All these happenings are properly contextualised by collecting the location and moment of the event. SensAI is focused mainly on:

Smooth HAI towards engaged empathetic relationship, reasoning about current emotional valence state of the human, and keeping all interaction very much passive only with seldom actions. The empathetic engagement relies on a score to be perceived by the human as the HAI empathy level. This metric is sensible to the frequency of human reporting. It decays over time (e.g., 24-hour cycle) and the decay rate may change with other actions, such as pausing the data collection. The agent writes some periodic messages using the in-application diary with useful information, such as the detected activity (e.g., running) and the current computed emotional valence value. All these actions, specifically empathy level notifications, are kept silent, only notifying when the human is interacting. Additionally, displays summary data such as physical activity by means of six recognised classes (e.g., walking) in a main dashboard. Also, a sentiment chart is available with interactive zoom and pan along the local memory chronological limit (e.g., 28 days) of sentiments reported and detected (e.g., Twitter status).

Efficient data collection as much as possible and allowed in a relatively low energy consumption. Accordingly, a practical data acquisition rhythm, such as $active = 2s$, $inactive = 8s$, $f = 1/5Hz$, and $D = 20\%$ is devised and implemented in order to acquire relevant data without too much power drain (below two-digit percentage points on average for several assessments). This rhythm and other thresholds (e.g., $100ms$ minimum interval between sensor fetches) may be subjected to automatic adaptation within environment changes. Regarding the sentiment analysis [14] of written texts, a custom heuristic is implemented [15] integrating language detection, translation, and emoticon processing. All in a best effort to get the sentiment value along with the language (English and Portuguese supported). This process adapts to the cases of mixed languages, emoticon-only text, and no language detected but emoticon available to extraction on analysing these short messages. Additionally, a display with the statistics about all sensors collected events is available. It includes sensor event count in local memory and already Cloud synced, last data sync, and percentage of collecting activity relative to application existence.

Environment adaptation in order to keep local resources healthy and survive to sudden contingencies, such as application crashes. An homeostasis-based implementation runs periodic checks, such as database health and data feed. It will take proper actions, such as recovering the data collection from sensors, and even a local database maintenance. The agent does a system registration at first start to deal with device boot and application upgrade special states. Also, guarantees the reviving by the Android operating system in cases of unexpected crash and removal from the running state. Regarding Cloud data syncing, it is robust to failures using a mechanism inspired in the relational database management system transaction. Only synced data will be marked for removal after local cache persistence threshold. Moreover, if no suitable data connection is available then it will adapt by increasing verification frequency for further try to sync. All these mechanisms of local cache and Cloud sync are paramount to keep healthy memory consumption and guarantee proper data collection.

B. SensAI Expanse

The Expanse comprises Cloud-expanded resources for the SensAI agent. These are able to supplement the smartphone restricted local memory, processing, and power. In a sense, it augments the agent cognition and memory. Regarding persistence, there is storage available for data since first value collected until the present. All data is secured and stored anonymously. Because of an efficient data collection, fewer data stored represents more after proper processing. There is a step during the machine learning pipeline where a transformation acts on cleaning and reconstructing collected data. This includes upsampling data within the actual thresholds previously used to save resources in the mobile device. Moreover, processing all eligible data through the available myriad of heuristics and other algorithms towards AutoML requires (a) an adaptation to the multiple human behaviours revealed in the data set; and (b) Bayesian efficient auto discovery on parameters.

The developed custom pipeline for SensAI learning uses various heuristics and other algorithms towards AutoML. These include data classes (negative, neutral, positive) imbalance (reports count) degree check from [19]. And also, a custom heuristic for class verification and learning process adaptation in cases, such as no reports for one (or even two) classes. After all these reasoning, the achieved entities are the ones eligible for the machine learning final step towards emotional valence prediction in context. Regarding location, the learn process make use of the unsupervised HDBSCAN algorithm clustering coordinates which accurately drops outliers. For each individual case, the relevant steps may be summarised as (a) calling HDBSCAN on provided `min_samples` (using $[1, 10, 100]$) in order to find the best `min_cluster_size` parameter; and before each call to the elected supervised multi-class classification algorithm Extreme Gradient Boosting (b) an auto search is run for the best cross validation K splits (K-fold) regarding the algorithm minimum count of accepted classes. Next, Bayesian optimisation is used for hyperparam-

eter auto tuning with cross validation for each specific model. Finally, the model fit for each human current data is achieved and performance metrics are computed. The actual knowledge from the learning process is stored efficiently with a very small memory footprint. The system prediction ability is ready to serve answers about contextualised emotional valence for each individual.

III. STUDY

This section encompasses the outcomes and method used in a research study running on a long-term interaction between SensAI and a population of human individuals in the field (anonymous participants outside the laboratory).

A. Method

The participants in this study are neither targeted nor recruited from anywhere. Instead, the goal to avoid a laboratory known [20] frequent bias of sampling only from Western, Educated, Industrialized, Rich, and Democratic (WEIRD) societies is accomplished by collecting data in the wild and worldwide. Smartphone sensing [21] is in place by means of an Android application. Moreover, privacy is enforced by removing all identifiable data before storing in Expanse. Furthermore, text in the Diary activity is kept local and will be destroyed by SensAI uninstallation. The user is informed on first install and by using the help option. A total of 57 participants (ten countries and four continents) installed SensAI, eight were discarded for not sharing age and gender thus 49 remained eligible for analysis before machine learning pipeline further restrictions. Moreover, some ten-year age range classes revealed to be under-represented hence a dichotomy approach is in place using age median ($M = 34$). Therefore, a reasonable distribution of all genders by the two age ranges, $[10, 34)$ vs. $[34, 70)$, is attained despite some gender disproportion in each range. The age range count relative difference from $[10, 34)$ to $[34, 70)$ is only 4.2% (one individual) as presented in Table I.

TABLE I. ELIGIBLE POPULATION FOR ANALYSIS

| | Age range | |
	$[10, 34)$	$[34, 70)$
Female	9	9
Male	15	16
Total	24	25

B. Results

Regarding the emotional valence states reported by the humans, there is evidence of valence proportion differences between some groups. In order to assess the statistical significance of this evidence depicted in Figure 3, the Mann-Whitney U test is used. The results presented in Table II show that the null hypothesis (H_0: two sets of measurements are drawn from the same distribution) can be rejected for all but two tests, i.e., evidence of significant differences on three comparisons of two groups each as described next:

$[10, 34)$ **vs.** $[34, 70)$ show differences between two age ranges mainly driven by the female gender.

$[10, 34)$ female **vs.** $[34, 70)$ female evidence a difference in behaviour where the older age group reported significantly less negative and neutral emotional valence and an order of magnitude more positive reports.

$[34, 70)$ female **vs.** $[34, 70)$ male evidence the overwhelming positive reports by female versus male in this age range group.
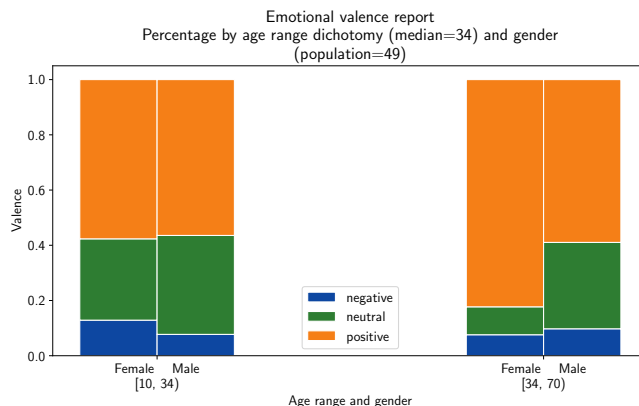

Figure 3. Emotional valence reports percentage by age range and gender.

TABLE II. AGE AND GENDER GROUPS COMPARISON (FIGURE 3): MANN-WHITNEY U TEST RESULTS

Age range and gender	p value	H_0 ($\alpha = 0.05$)
$[10, 34)$ vs. $[34, 70)$	1.161×10^{-30}	rejected
$[10, 34)$ female vs. $[34, 70)$ female	5.539×10^{-14}	rejected
$[10, 34)$ male vs. $[34, 70)$ male	1.561×10^{-1}	not rejected
$[10, 34)$ female vs. $[10, 34)$ male	3.938×10^{-1}	not rejected
$[34, 70)$ female vs. $[34, 70)$ male	7.027×10^{-67}	rejected

Regarding the system prediction performance, a previous study [15] revealed Extreme Gradient Boosting with F1 score as the best option on average for the population individuals, as already depicted in Figure 2. The sample is reduced to 31 eligible individuals due to valence classes imbalance restrictions further applied in the machine learning pipeline process. Regarding these entities, the high scores achieved were independent of age and gender, no pattern whatsoever was revealed. Further, inspection of the feature importance contribution to the prediction revealed that most of the population is more sensible to the time dimension than the location. Specifically, weekday (`moment_dow`) is the most, 64.5% of the cases, influential for emotional valence predictions followed by hour (`moment_hour`) with 25.8%, and location (`mgrs_...`) with 9.7%. This ranking is obtained using SHapley Additive exPlanations (SHAP) on all entities prediction model for the feature ranked first on each entity. Meaning that for almost all entities the moment, weekday and hour, is decisive to obtain a prediction whereas for a few (e.g., entity 5 as depicted in Figure 4) some locations strongly compete for emotional valence prediction.
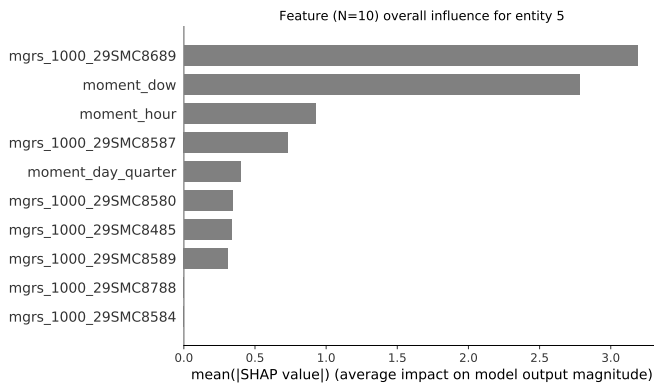
Figure 4. Feature overall influence for entity 5.

Regarding the common behaviour, entity 24 is a typical individual where the time dimension prevails on emotional valence prediction. In this case, Sunday is a weekday where all locations are expected to have positive value predictions. Accordingly, Figure 5 shows the expected positive emotional valence on a Sunday in the future at 8:00 a.m. for the top seven locations (most influential).

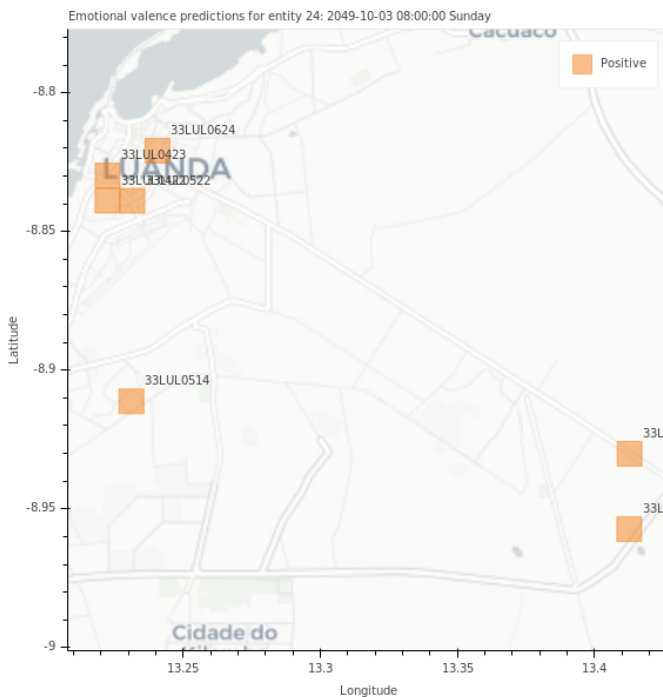Figure 6. Entity 24: Tuesday valence probability for the top 7 locations.

Figure 5. Entity 24: Sunday valence probability for the top 7 locations.

Regarding the same top seven locations and hour of the day, Figure 6 depicts a quite different day from the previous Sunday. The computed probabilities are in order with the expected for a business day for this entity at 8:00 a.m.

The map areas of emotional valence prediction measure $1000\,\mathrm{m}$ square side due to reasonable cell size for same place sentiment and a feasible number of cells able to use as features in the learning pro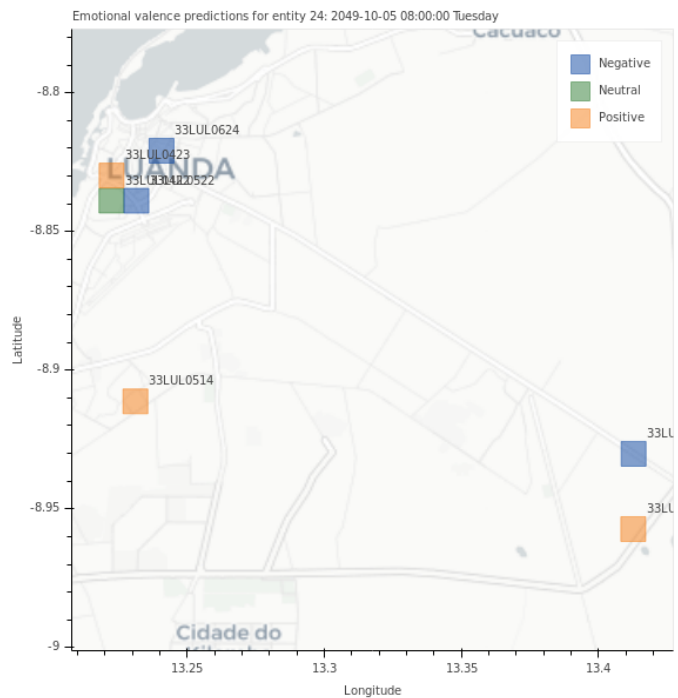cess. Moreover, world map is divided into cells following the Military Grid Reference System (MGRS). These maps are obtained with a developed prototype (Jupyter notebook and Python) for prediction analysis online using the last AutoML results for each entity. The tool is interactive including zoom and more information on hover each location.

Every scientific study has limitations. In order to clarify under which conditions the results should be interpreted, the identified limitations of the present work are (a) no prior health information about the users that may impact the engagement effect including prediction result bias; (b) interacting with a non-anthropomorphic versus human-like agent [22] may impact the emotional valence state reported; and (c) affective reactivity and regulation gender differences on emotional response to context are not considered as proposed in [23]. Although, gender and age neutrality is achieved by SensAI+Expanse results on predicting emotional valence states. Moreover, there is no evidence of any bias in the prediction scores achieved regarding the individual gender.

IV. CONCLUSION AND FUTURE WORK

This paper described the SensAI+Expanse system ability to predict emotional valence states (a) in spatial and temporal context; (b) with very good performance; and (c) age and gender neutral on revealing some individuals' idiosyncrasies. Moreover, this smartphone sensing-based system is robust to unexpected behaviours from humans, Cloud, and mobile demanding environments. The SensAI agent first adapts to the operating system restrictions on mobile resources use, such as keeping battery consumption below two-digit percentage points on average. Then, it uses a myriad of heuristics and

other algorithms in order to achieve the best possible prediction whichever human behaviour encounters within the collected data. The outcomes presented show evidence, restricted to population and data samples in this study, of differences in behaviour amongst some combinations of age ranges versus gender. Regardless, SensAI+Expanse was able to adapt and learn to predict emotional valence states with very good scores for every individual on average (Figure 2). Thus, SensAI is able to reveal idiosyncratic factors on human's emotional valence changes without any bias regarding age and gender. Moreover, adding features to the learning process may reveal distinct factors not yet discovered, such as influence of physical activity (e.g., riding a bike). The accelerometer data may be used to correlate physical activity with valence (positive) state [24]. This course of action may be taken as future work. Therefore, SensAI+Expanse contributes as a novel platform for affective and cognitive studies about human emotional valence changes in context. Further, it may complement and eventually supersede laboratory usually long-list self-appraisal questionnaires. Moreover, it reinforces smartphone sensing contribution as a tool for personalised health studies, such as emotional disturbances accompanied by healthcare professionals. Furthermore, all the source code is published as free software under the Apache License 2.0. Future work may include prior health information from each human. Thus, adapting interaction and learning process towards better predictions. Furthermore, SensAI may enable classifying options (e.g., Likert scale) at some specific events for the human to grade the agent behaviour hence tailoring future actions. This course of action may diminish the identified limitations described in the previous section and contribute to better studies.

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